3-2019

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ABSTRACT

Big data have become available in all kinds of healthcare organizations. The application of big data analytics in Managed Care Organizations (MCOs) has the potential to improve health care, lower costs, save lives, and help to make better-informed decisions. The study illustrated the implication of big data in MCOs. Big data can help MCOs reduce patients' relevance, analyze specific diseases such as asthma and diabetes. Big data also could help MCOs to reduce cost after collecting data and determined the specific patients' situation. The implication of big data has benefited MCOs in reducing costs, improving the quality of healthcare care. Interview content, limitation, and practical implication of this study are further discussed.

Keywords: *Big data, data analytics, managed care, costs, quality, diabetes, influenza,*

INTRODUCTION

"Big Data" is a term used to describe massive data sets which have more varied, large and complex structure and are not able to be stored, analyzed and visualized or cannot be processed efficiently by traditional data management tools (Sagiroglu & Sinanc, 2013). The core features of big data could be summarized as the five Vs., which are Volume, Variety, Velocity, Veracity, and Value (Demchenko, Grosso, De Laat, & Membrey, 2013). Managed Care Organizations (MCOs) have been defined as systems that integrated the financing, insurance, and delivery of healthcare services (Ridic, Gleason, & Ridic, 2012). It was created to furnish the health care services to covered individuals, establish selection criteria for health care providers, create programs for processing utilization review and quality assurance, and encourage members to use providers and procedures which were associated with their plans by financial incentives (Shmueli, Stam, Wasem, & Trottmann, 2015). Big data have become available in all kinds of healthcare organizations and has become necessary as deriving insights to improve healthcare delivery and reduce waste (Sun & Reddy, 2013).

According to Konstvedt (2015), managed care has gradually replaced fee-for-service and other traditional health care plans from 27% in 1988 to 80% in 2013. Although the rate of managed care has started to decrease from 95% in 2003 because of the appearance of High-Deductible Health Plans with Savings Option (Konstved, 2015). Also, Preferred Provider Organizations (PPOs) with 57% and Health Maintenance Organizations (HMOs) with 14% have been the most prevalent types of MCOs in U.S. healthcare systems (Claxton et al., 2013).

IBM has indicated that 2.5 exabytes (10^{18} bytes) of data are created every day, and 90% of the data produced in the last two years (Bhagat, 2015). In 2012, digital world of data was expanded to 2.72 zettabytes (10^{21} bytes), and it would spend about 20 billion personal computers to store the data around the world (Sagiroglu & Sinanc, 2013). Data from U.S. healthcare systems reached 150 exabytes in 2011, and at this rate of growth, the number would soon reach the zettabyte (1021 gigabytes) scale, even the yottabyte (1024 gigabytes) (Cottle, Kanwal, Kohn, Strome, & Treister, 2013).

Big data has become a trendy topic in healthcare, and the term primarily referred to the vast and growing volumes of computerized medical information, such as drug and disease monitoring registries, Electronic Health Records (EHRs), and administrative or health claims data (Trifirò, Sultana, & Bate, 2017). Big data in healthcare generally has been collected through clinical practice and administration processing by different healthcare professionals, such as pharmacists registering prescriptions, and physicians recording the drug prescriptions, medical history, or medical claims of their patients (Trifirò et al., 2017). The study from Futrel (2014) predicted that the share of data for medical use would be a fourfold increase from 2012 to 2020, but healthcare as one of the largest data producers, it has been the least prepared industries to handle the remarkably increasing data. Also, big data has been collected without being used which should be fully recognized by health care organizations for a long time (Trifirò et al., 2017).

Accountable Care Organizations (ACOs) have been using big data technologies to reduce healthcare costs and improve the quality of healthcare; in addition, ACOs have established Big Data warehouses to optimize health care services (Tomar, Chaudhari, Bhadoria, & Deka, 2016)

A study from Frakt and Pizer (2016) have suggested that big data would rapidly improve healthcare delivery. Big data analytics have the potential to improve health care, lower costs and save lives, and the application of big data analytics in MCOs and ACOs could help to make better-informed decisions (Dembosky, 2012). Driven by mandatory requirements and the potential to improve the quality of healthcare delivery as well as reducing the costs, these massive quantities of data hold the promise of supporting a wide range of medical and healthcare functions, including clinical decision support, disease surveillance, and population health management (Dembosky, 2012). Institutions and organizations might get benefits from big data analytics for their future directions, development, decisions, investments, and challenges with predictive as well as descriptive analytics, such as healthcare systems, user behavior analysis, decision support systems, personalized systems, and market analysis (Sinanc, Demirezen, & Sagiroglu, 2016).

The purpose of the research was to determine whether big data and data analytics could reduce the costs of health care, improve the quality of care, and control overutilization within MCOs.

METHODOLOGY

The primary hypothesis of this paper was that big data would be helpful for reducing unnecessary health care costs and improving the quality of healthcare within MCOs. The secondary hypothesis of this research was that big data and data analytics would play an essential role in reducing patients' prevalence and analyzing specific disease such as diabetes for MCOs. The methodology of this study was a literature review which could be separated into three steps: (1) identifying literature and collecting data, (2) establishing criteria for the literature analysis and evaluation, (3) categorizing literature. Also, a semi-structured interview has been done via telephone for this research on March 27, 2018. Grace Sun, an expert in big data which works at a kidney dialysis center (Satellite Healthcare) in San Jose, California, was the person participated in the semi-structured interview, and the interview has been recorded for the literature review. Eight questions such as the interviewee's work experience, facts, and opinions about big data, and how her organization uses big data were chosen for this interview.

Step 1: Literature Identification and Data Collection

The key terms used for literature identification were "big data" OR "data analytics" AND "managed care" OR "managed care organizations" OR "PPOs" OR "HMO" OR "health care" AND "costs" OR "quality" OR "diabetes", such as Academic Search Premier, PubMed, ProQuest, ScienceDirect, and Google Scholar. Reputable websites such as the Agency for Healthcare Research and Quality, Health Affairs, American Telemedicine Association, and CDC were also used in the search. Citations and abstracts of articles were assessed to identify whether they could satisfy the requirement of this study.

Step 2: Literature Analysis and Evaluation

The identified literature for the study was limited to big data and managed care. The abstracts of academic articles and studies were reviewed first to examine the relationship of their content with the topic. If the abstracts were found to be appropriate to the topic, the articles would be analyzed. To stay with current trends to the topic, articles only published from 2007 to 2018 were chosen in this research. The literature evaluation and analysis were limited to the articles which were written in the English language and full texts, and a total of 31 references were used in this study. L.X. and W.B. did the literature search, and it was validated by A.C. who acted as the second reader and double-checked whether all the references met the inclusion criteria of the research study.

Step 3: Literature Categorization

After analyzing the articles, useful articles were selected and categorized into three sections based on the findings, which included the application of big data for reducing patients' prevalence, application of big data for analyzing special diseases, and application of big data for reducing healthcare costs

RESULTS

The application of big data can help MCOs improve their service quality and reduce costs by analyzing specific disease and high-risk people. Meanwhile, big data can help MCOs to decrease rates of patients' prevalence. The primary studies showing the application of big data in MCOs were classified by the purpose and the outcomes and summarized in Table 1 (Table 1).

Application of Big Data for Reducing Patients' Prevalence

In the report from Grohskopf et al. (2016), big data was used to preventing influenza. According to the data collected by ACIP from more than 30,000 patients, the vaccine HD-IIV3 seemed to be efficient to adults elder than 65 years old; and RIV4 was more effective compared to IIV4. According to a study of the effectiveness of RIV4 and IIV4 from 2014 to 2015, 4,303 patients accepted RIV4 and 4,301 patients accepted IIV4, the result showed RIV4 was 36% effective and IIV4 was 4% effective. In another study from 2009 to 2010 in 6,107 patients with HD-IIV3 and 3,051 patients with vaccine SD-IIV3, this kind of vaccine was not effective against patients elder than 65 suffered from pdm09 (Grohskopf et al., 2016). Since viruses such as A/Michigan/45/2015 (H1N1) pdm09–like virus should be included in the vaccines from 2017 to 2018, FluMist Quadrivalent (LAIV4; MedImmune, Maryland) should not be applied in 2017 and 2018 since this kind of vaccine seemed not effective against A(H1N1) pdm09 viruses (Table 1).

Glanz et al. (2013) conducted a study with eight MCOs investigating the vaccination by using big data collected from more than 400,000 children born between 2004 and 2008. The results of this study indicated that nearly 50% of these children were under-vaccinated before 24 months. Compared to unvaccinated children, vaccinated children had a 95% lower outpatient visit rate compared to unvaccinated children (Glanz et al., 2013). Also, by reviewing the big data collected from more than 1,000 medical records from more than 150,000 children, the researchers also found that most nonmedical reasons came from the parents' rejection (Glanz et al., 2013). The results of this study showed the essentialness of children before 24 months accepting vaccines (Table 1).

Other studies such as Hechter's study found that Hepatitis B can be effectively reduced by using the vaccine. Less than half of the patients in more than 15,000 patients suffered from Hepatitis B after the accepted vaccine (Hechter et al., 2014). While in Abara, Qaseem, Schillie, McMahon, and Harris (2017) study, they use big data to give suggestions to avoid suffering from Hepatitis B. Bayen, Jacquemot, Netscher, Agrawal, Noyce, and Bayen (2017) conducted a study analyzing falls' threat. According to this study carried out in a Californian memory care organization, both fatal and nonfatal injuries may happen to people elder than 65 because of the falls. Falls has resulted in the costs of $637.2 million for fatal falls and $31.3 billion for nonfatal falls every year. So, avoiding falls for older adults was helpful to avoid injuries (Bayen et al., 2017).

Application of Big Data for Analyzing Specific Diseases

Big data has played an important role recently in treating asthma (Barrett et al., 2013). Barrett, Humblet, Hiatt, and Adler (2013) found that more than 25 million Americans were suffering from asthma. According to a study conducted by Farber, Batsell, Silveira, Calhoun, and Giardino (2014), the possibility of patients whose mother is a smoker to suffer asthma increased by 95% in more than 22,000 patients. The result of this study showed tobacco had a significant influence to increase the possibility for children to suffer asthma (Table 1). In another study analyzing asthma, patients' condition was better after their controlling to asthma improving from 38% to 75% in the period of study (Sickle, Maenner, Barrett, & Marcus, 2013).

Two articles from Lawrence et al. (2014) and Falen, Noblin, Russell, and Santiago (2018) both mentioned the implication of big data in MCOs. In Lawrence's study, EHRs provided by MCOs can offer an efficient source of data while analyzing childhood diabetes surveillance. According to Lawrence et al. (2014), among nearly 800,000 young people, 77.2% of them were type 1 diabetes, and 22.2% were type 2 diabetes (Table 1). In another study, EHRs could allow monitoring or surveillance to prevent postoperatively and to reduce the numbers of postoperative infections like superficial incisional surgical site infections and deep incisional surgical site infections (Falen et al., 2018).

The expert in big data also illustrated the implication of big data in analyzing kidney disease. More than 50% of patients may have symptoms such as urination changes. According to Expert, more than 80% percent of patients who need a kidney needed to wait about four years. She also stated that although her organization has implicated big data less than five years, big data has helped her clinic to prevent medical errors, identify high-risk patients, reduce costs, improve productivity, and enhance patient outcomes.

Application of Big Data for Reducing Healthcare Cost

The adoption of EHRs has facilitated the application of big data. Researchers have found that EHRs and big data can offer MCOs the potential for cost savings (Bates, Saria, Ohno-Machado, Shah, & Escobar, 2014; Raghupathi & Raghupathi, 2014). A predictive system based on big data could identify practical use cases such as high-cost patients, triage, adverse events, and diseases with the treatment influenced by multiple organ systems (Bates et al., 2014). In the example listed by Raghupathi & Raghupathi (2014), big data was used to reduce nearly $7 billion in healthcare spending (Raghupathi & Raghupathi, 2014).

Spyropolos & Lin (2007) calculated the cost of patients with deep vein thrombosis and pulmonary embolism. Nearly 1.5,000 patients in 30 MCOs participated in this study. The rate of readmission for patients who were primarily diagnosed with a deep vein thrombosis or pulmonary embolism was more than five percent. The rate of the readmission for those who were secondly diagnosed with a deep vein thrombosis or pulmonary embolism was nearly 15% in a year (Spyropoulos & Lin, 2007). Totally, more than 50% of all hospital readmissions for deep vein thrombosis and nearly 60% for pulmonary embolism happened in the first 90 days after the initial event. As for the cost, the total cost of readmission for patients with a deep vein thrombosis was more than $2,000 staying in hospital for 7.7 to 8.7 days; the total cost of readmission for patients with pulmonary embolism was nearly $15,000 with a staying in hospital last for 7.4 to 7.6 days (Spyropoulos & Lin, 2007). By using these big data to analyze the possibility of readmission for patients with deep vein thrombosis or pulmonary embolism, it was possible for these MCOs to predict and save their cost (Table 1).

According to the expert in big data, MCOs need to use big data because it can help to reduce the cost. MCOs had departments like marketing, administrating and other financial officers who needed big data to help their work to become more active and productive. By dealing with the patients' feedback, MCOs are convenient to analyze sentiments and identify patterns. Her clinic already set a specific strategic plan towards implication of big data and big data will help them to reduce more cost in the future. Because the more data they collect and use, the more accurate conclusion they will have, the more proper decision they will make.

Other researchers also have used big data to analyze the cost of MCOs for some specific diseases. Kim, Lin, Hussein, Kreilick, and Battleman (2009) of atrial fibrillation in the hospital should be changed since it made a heavy burden on MCOs. According to Kim et al. (2009), inpatient cost for primary atrial fibrillation more than 11 thousand dollars while outpatient costs were $2826.78 in a year. For hospitalized patients with secondary atrial fibrillation, the total cost was more than $6557.

Application of Big Data for predicting mortality

Another important application of big data is in predicting mortality (Schneeweiss, 2014). The method of collecting the amount of data and applied it to predict patients' outcomes has already existed years ago. According to some articles in the past, severity of illness (SOI), Acute Physiology and Chronic Health Evaluation (APACHE), and Simplified Acute Physiology Score were all the examples of collecting data and implementing it (Knaus, Zimmerman, Wagner, Draper, & Lawrence, 1981; Le Gall, Loirat, & Alperovitch, 1983). However, instead of relying on static models manually collecting from patient datasets, collecting personalized information in big health data from electronic medical records (EMRs) and other monitoring devices seemed more helpful in predicting patients' outcome (Lee, Maslove, & Dubin, 2015).

Lee, Maslove, and Dubin (2015) conducted a study to measure the relationship between predictive performance and the number of patients collected in the data. According to their study, which based on 29.149 adults at the Beth Israel Deaconess Medical Center (BIDMC) in Boston, the predictive performance increased with the increasing of patients but declined after the peak point. By calculating the area under the receiver operating characteristic curve (ROC) and the area under the precision-recall curve (PRC), the peak was achieved while the data collected from 6,000 patients were used (the most significant area under ROC was 0.83, and the larges area under PRC was 0.47). After that point, these two characters were declined while the number of patients was increasing (Lee et al., 2015). They concluded that the mortality prediction performance would be better if big data collected from similar patients rather than a more significant number of patients were used.

In another study conducted to measure the predictive mortality performance in hospital emergency department, there were more than 4,000 visits in the derivation group, and 5% of these patients died during hospitalization; while in the validation group, 4.7% of 1,056 patients died (Taylor et al., 2016). The area under the curve (AUC) was used to measure the mortality predictive performance. Compared to traditional methods, random forest model performed best with a 0.860 AUC, while MEDS score got 0.705, REMS score got 0.717, and CART model got the smallest area under the curve with the number of 0.693 (Taylor et al., 2016). As a result, the random forest model driven by big data performed better than other traditional analytic models in predicting in-hospital mortality (Taylor et al., 2016).

Researchers in other countries also found that big data can help to predict mortality. In Spain, some researcher concerned older adults' mortality with big data (Pinzon et al., 2016). They analyzed 142,028 women and 58,011 men, whose average age was 80 years. They found that women's death risk is 38% less than men; nursing home care increased mortality more than a half compared to home-based care. Meanwhile, the activities of the daily living level, age, and chronic obstructive would also influence the risk of death.

Table 1: The Summarize of Articles on Big Data Application in Managed Care Organizations

Application of Big Data	**Author/Year**	**Design aim**	**Key Findings**
The effectiveness of the vaccine	Glanz et al. (2013)	●	● The vaccine was effective for children before two years' old ● Most common reason for unvaccinated children was parent's rejection ● Nearly 50% of 400,00 children were under-vaccinated before 24 months ● Vaccinated children had a 95% lower outpatient visit rate compared to unvaccinated children
	Grohskopf et al. (2016)	●	● RIV4 was 36% effectiveness, and IIV4 was 4% effectiveness in totally 8.600 patients ● Pregnant women should accept the specific vaccine

			● RIV4 was more effective than IIV4 for people older than 65 in treating H1N1. ● Vaccines in treating A/Michigan/45/2015 (H1N1) pdm09 should be included from 2017 to 2018
Analyzing diseases	Farber et al. (2014)	●	● the possibility of patients whose mother is a smoker to suffer asthma increased by 95% in more than 22,000 patients ● tobacco could increase the possibility for children to suffer asthma
	Lawrence et al. (2014)	●	● 77.2% of young people were type 1 diabetes, and 22.2% were type 2 diabetes in nearly 800 thousand young people
Reducing cost	Spyropolos & Lin (2007)	●	● Patients diagnosed with a deep vein thrombosis or pulmonary embolism were more than five percent in 1.5 thousand patients ● The rate of the readmission for patients secondly diagnosed with a deep vein thrombosis or pulmonary embolism was nearly 15% in a year ● The extra cost caused by readmission was nearly $15,000 with a staying in hospital last for 7.4 to 7.6 days ● Totally, more than 50% of all hospital readmissions for deep vein thrombosis and nearly 60% for pulmonary embolism happened in the first 90 days after the initial event.
	Kim et al. (2009)	●	● Big data could help MCOs organizations in substantial saving. ● Inpatient cost for primary atrial fibrillation was more than 11,000 dollars, and outpatient costs were $2826.78 per year. ● For hospitalized patients with secondary atrial fibrillation, the total cost was more than $6557.

DISCUSSION

This article proposed to state and clarified the implication of big data in MCOs. The hypothesizes of this paper can be divided into two parts: big data would be helpful to reduce unnecessary health care costs and improve the quality of healthcare within MCOs, and big data and data analytics would play an essential role in reducing patients' prevalence and analyzing specific disease such as diabetes for MCOs.

The results of this paper can be concluded into four parts. The results of the interview showed that big data was useful in MCOs in helping reduce patients' prevalence, analyzing specific disease, and reducing cost. The literature review showed that big data could be helpful in reducing patients' prevalence, analyzing specific disease, and reducing healthcare costs.

The expert in big data (2018) stated that the opinions that satellite healthcare in California has applied big data for less than five years, and big data did help to their jobs by collecting data and analyzing the kidney disease such as kidney's symptoms. She held the view that there might be some limitations in applying big data since the collection of data may be limited, but big data would be used frequently and meaningfully in the future.

However, without the right information technology infrastructure, workflows, analytic tools, and visualization approaches, the insights provided by big data might be limited (Roski, Bo-Linn, & Andrews, 2014). To guarantee the application of big data by MCOs, many current practices and policies related to data use, access, sharing, privacy, and stewardship need to be revised.

Study limitation

This literature review was limited since the limitation of the search strategy used, such as the number of articles searched, the number of databases available. Meanwhile, the publication and the researcher bias may have influenced the quality and the opinions of these articles. Furthermore, although the studies and articles used in this article are concerned about the use of big data in MCOs, not many studies described the process of big data's collection, which resulted in the lack of description of data collecting in this article. Last, the interviewer worked in a kidney dialysis center, which made the expert focusing more on the implication of big data in kidney disease.

Practical Implication

Big data has the potential to create significant value in healthcare (Lee & Yoon, 2017). The benefits of using big data by MCOs are improving the quality of healthcare, analyzing some chronic diseases, and reducing unnecessary healthcare costs as well as the patients' prevalence. Also, MCOs might make a better decision by big data analytics because they can review the results of big data analytics more directly and immediately.

CONCLUSION

Big data has been widely implemented in MCOs, and the main three advantages of using big data within MCOs were reducing patients' prevalence, analyzing specific diseases, and reduce the organization's cost.

Expert in big data. (2018). Grace Sun, Satellite Healthcare, personal communication. March 26, 2018.

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